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An EMD-Average Algorithm and its Application in Bearing Fault Diagnostics under Time-Varying Rotational Speed Condition

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Abstract:
The load variation causes the change of rotational speed in rotary machines and in this time the fault features of bearing are not periodic. In order to realize a fault diagnostics of bearing, in this paper Empirical Mode Decomposition algorithm based on average of maximum and minimum (EMD-average algorithm) is proposed. First a vibration signal of rotary machine is decomposed into several Intrinsic Mode Functions (IMFs) through EMD-average algorithm. Next Hilbert transform is applied on IMFs to calculate the Instantaneous Rotational Frequency (IRF) of bearing and then the fault characteristics of bearing are detected from IRF. MATLAB simulation and experiment results show that the proposed EMD-average algorithm outperforms than classical EMD algorithm and EMD-midpoint algorithm from the viewpoint of iteration number and frequency decomposition.

Keyword: EMD-Average Algorithm, Fault Diagnostic, Bearing Fault

1. Introduction

Empirical Mode Decomposition (EMD) is widely used in fault diagnosis of rotary machines such as a bearing or gear [1]. However, the realization of EMD requires a generation of upper and lower envelopes. In this time, not only it has under shoots and upper shoot, but also requires great computing time. The study on bearing fault diagnosis by using EMD was performed into two sides.

One of these is to reduce the amount of calculation through a modification of EMD algorithm or to reduce the error through an envelope interpolation method.

Mayer Humi proposed the EMD-midpoint algorithm as a variety of EMD [2]. In this algorithm, the averages of upper and lower envelopes at each point replaced with the value of midpoint between consecutive local maxima and local minima. Yongbo Li et al. proposed the bandwidth based EMD (BEMD) [3]. In this method, optimal Intrinsic Mode Functions (IMFs) with minimal frequency bandwidth was selected from IMFs which resulted using seven envelope interpolation methods.

Through this processing, the mode mixing problem was alleviated and more accuracy of decomposition was obtained.

However, the composition performed by using seven envelope interpolation methods, so the envelope calculation requires more times than classical EMD and the real time fault diagnosis is difficult.

In order to overcome the envelope problem in EMD, the optimized rational Hermite interpolation method proposed [4]. This method has higher accuracy and reliability than classical EMD.

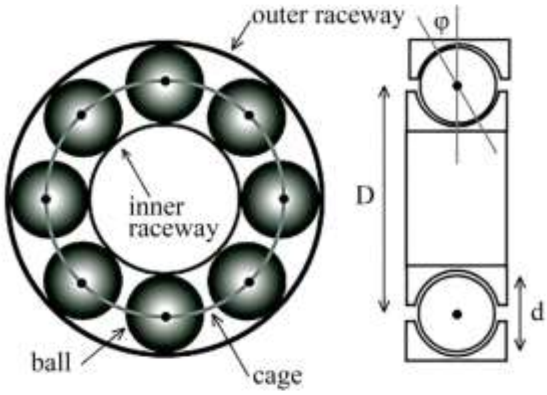
Another of these is to perform the bearing fault diagnosis through combination of EMD and the other methods.
Amarnath et al. obtained IMFs from vibration and acoustic signals by using EMD and then performed a fault diagnosis with extracted statistical parameters from IMFs such as a kurtosis [5].
Junsheng et al. separated the background, noise and rub-impact signals from vibration signal of rotor system by using EMD and extracted rub-impact fault features through Hilbert transform [6].
Renping et al. applied the wavelet threshold de-noising to high frequency IMF resulted from signal through EMD and extracted fault features by using a short-time Fourier transform (STFT) [7].
As a result, the signal-to-noise ratio of signal was largely improved and the fault feature effectively extracted.
In [8], the nonlinear response of rotator decomposed into IMFs by using EMD and the maximal local Lyapunov exponent based prediction result of IMF obtained. The nonlinear response of cracked rotor was predicted through summing prediction results of every IMF.
However, this method has great error. In [9], the features closely related to the fault ware extracted by applying of distance evaluation technique for IMF resulted from EMD. In this method the fault diagnosis was performed by using multi-class transductive support vector machine (TSVM).
This method has an advantage of high accuracy and drawback of much calculation amount.
To guarantee an orthogonality of non-stationary time series and overcome the generation of redundant components, Fengli et al. used a combination of independent component analysis (ICA) and EMD [10].
This method also has a drawback of much amount of calculation, because ICA includes a matrix calculation.
In order to extract a fault features of roller bearing, Junsheng et al. first extracted IMFs of a vibration signal by using EMD and then made autoregressive (AR) model for IMFs [11].
Next, they performed the fault diagnosis of roller bearing through Mahalanobis distance calculation for AR parameters regarding as the feature vectors.
This method requires much calculation times in AR modelling and fault diagnosis.
On the other hand, EMD and Hilbert Transform (HT) are widely used for extracting of a fault features included in nonlinear and non-stationary signals [13, 14, 15].
However, EMD requires large computational cost and it may generate undesirable IMFs.
Therefore, in order to realize a tachometer-free bearing fault diagnostics under time-varying speed conditions by using EMD, have to work out following problems.
(1) Reduction of computation amount in EMD processing
(2) Extraction of bearing fault characteristics
The method to solve those problems presented in this paper.

2. Related research work

2.1 Fault classification and fault feature frequency of rolling-element bearing

This paper considers rolling-element bearings and Figure1 shows the geometry of rolling-element bearings.

Figure1. Geometry of a Rolling-Element Bearing



The bearing consists mainly of the outer and inner raceways, the balls, and the cage, which assures equidistance between the balls.
Bearing faults can identify according to the fault characteristic frequency (FCF).
Generally, almost faults of bearing are the outer and inner faults.
For a bearing with fixed outer race and rotating inner race, the FCFs of an outer race fault and an inner race fault are follows [15-17].

$$BPFO = \frac{n_b}{2}\left(1 - \frac{d}{D}\cos\phi\right)f_r \tag{1}$$

$$BPFI = \frac{n_b}{2}\left(1 + \frac{d}{D}\cos\phi\right)f_r \tag{2}$$

(BPFO: Ball passing frequency outer race, BPFI: Ball passing frequency inner race)
On the other hand, the FCF of ball is follows [16,17].

$$BSF = \frac{D}{2d}\left\{1 - \left(\frac{d}{D}\right)^2 \cos^2\phi\right\}f_r \tag{3}$$

(BSF: Ball spin frequency)
Also the FCF in a cage is follows [16].

$$FTF = \frac{f_r}{2}\left\{1 - \frac{d}{D}\cos\phi\right\} \tag{4}$$

(FTF: Fundamental train frequency)
where n_b is the number of rolling elements, d is the diameter of the rolling element, D is the pitch diameter of the bearing, ϕ is the angle of the load from the radial plane, and f_r is the shaft rotational frequency.

As can see in Eqs (1)-(4), the FCFs are proportional to a shaft rotational frequency.
So if we get a shaft rotational frequency, then can diagnose the bearing fault from FCF.

2.2 Bearing fault characteristic extraction by using HT

Generally, the HT for any signal $x(t)$ is

$$H[x(t)] = y(t) = \frac{1}{\pi}\int \frac{x(\tau)}{t-\tau}\, d\tau \tag{5}$$

where $H[\bullet]$ denotes the HT operation.

Theoretically, any analytic signal $z(t)$ can be expressed by the sum of its real part $x(t)$ and imaginary part $y(t)$ which is the HT of the real part. So

$$z(t) = x(t) + jy(t) \tag{6}$$

Equation (6) can be rewritten in a polar coordinate system as

$$z(t) = a(t)e^{j\theta(t)} \tag{7}$$

where

$$\begin{cases} a(t) = \left[x^2(t) + y^2(t)\right]^{1/2} \\ \theta(t) = \tan^{-1}\left(\dfrac{y(t)}{x(t)}\right) \end{cases} \tag{8}$$

represents the instantaneous amplitude and phase of the analytic signal, respectively.

From the instantaneous phase $\theta(t)$, the instantaneous frequency $\omega(t)$ of the signal can be derived as

$$\omega(t) = \frac{d(\theta(t))}{dt} = \frac{\dot{y}(t)x(t) - y(t)\dot{x}(t)}{x^2(t) + y^2(t)} \tag{9}$$

Accordingly, the real part of the signal $x(t)$ can be written in terms of the amplitude and instantaneous frequency as a time dependent function

$$x(t) = \Re(z(t)) = \Re\left(a(t)e^{i\int \omega(t)dt}\right) \tag{10}$$

where the symbol $\Re(\bullet)$ denotes the real part of the analytic signal $z(t)$.

From an instantaneous frequency, FCF can be calculated by using (1)-(4).

2.3 Classical EMD algorithm

Generally, the HT is not applicable for non-stationary data series [14].

However, every IMF component from EMD decomposition is stationary, then the HT of the IMF component can reflect the actual physical background, and the corresponding Hilbert spectrum can exactly illustrate the distribution of power on various scales of space or time in the physical phenomenon.

That is, the EMD method is a basis to carry out the HT for non-stationary data series.

The idea of EMD is to extract a new intrinsic mode functions (IMFs) from a signal.

After a number of iterations of extraction, the characteristics of the IMF have to meet the two conditions:

(1) in the entire data set, the number of extremes and the number of zero crossings must either be equal or differ by at most one, and

(2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The classical EMD algorithm consists of following steps [8].

Step 1: Identify all the local maxima and local minima of $x(t)$ and then connect all the local maxima by a cubic spline line as the upper envelope and all the local minima as lower envelope.

Step 2: Compute the mean value $m_1(t)$ of the upper and lower envelopes

Step 3: The difference between $x(t)$ and $m_1(t)$ is noted as $h_1(t)$.

That is

$$x(t) - m_1(t) = h_1(t) \tag{11}$$

In the ideal case, if $h_1(t)$ is an IMF, then $h_1(t)$ is the first component of $x(t)$.

Step 4: If $h_1(t)$ is not an IMF, $h_1(t)$ treats as the original signal.

Repeating steps (1)-(3), we can get

$$h_1(t) - m_{11}(t) = h_{11}(t) \tag{12}$$

where $m_{11}(t)$ is the mean value of upper and lower envelopes of $h_1(t)$.

After repeated sifting, i.e. up to k times, $h_{1k}(t)$ becomes an IMF.

$$h_{1(k-1)}(t) - m_{1k}(t) = h_{1k}(t) = c_1(t) \tag{13}$$

The first IMF component obtained from the original data $c_1(t)$ should contain the highest frequency component of the signal.

Step 5: Separate $c_1(t)$ from $x(t)$ and we can get

$$r_1(t) = x_1(t) - c_1(t) \tag{14}$$

where $r_1(t)$ is treated as the original data. Repeat the above processes.

Hence, the second IMF component $c_2(t)$ of $x(t)$ can be obtained.
Repeat the above process for n times, then nth IMFs of signal $x(t)$ can calculate.
Then

$$r_2(t) = r_1(t) - c_2(t) \tag{15}$$
…
$$r_n(t) = r_{n-1}(t) - c_n(t) \tag{16}$$

The decomposition process continues until $r_n(t)$ becomes a monotonic function which no more IMF can be extracted. Therefore, the signal is

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) \tag{17}$$

So the signal can be decomposed into n empirical modes and residue $r_n(t)$.
The IMFs include different frequency bands ranging from high frequency to low one.
The frequency components contained in each frequency band are different and change with the variation of a signal $x(t)$.

2.4 EMD-midpoint algorithm

In the classical EMD algorithm, its decomposition processing is failed in many cases where the data contains two or more frequencies which are close to each other.
The essential of EMD-midpoint algorithm is to replace the mean of upper and lower envelopes to spline curve of signal values at a midpoint between adjacent local minima and maxima.
In this algorithm, the step 1 and step 2 of a classical EMD is modified following as [2].
Step 1: Find the midpoints between two adjacent local maxima and local minima.
And the value of $x(t)$ at that point is noted as N_k.
Step 2: Create the spline curve m_k that connects the points N_k.

2.5 Proposed EMD-average algorithm

For the data contains two or more frequencies which are close to each other the EMD-midpoint algorithm is not decomposed frequency components.
To solve this problem, the step 1 and step 2 of EMD-midpoint algorithm is modified following as.
Step 1: Compute the average value of adjacent two local minima and maxima and find the interpolation points.
If the calculated average value exists in a signal value series, then the sample point with an average value is selected as interpolation point.
Else if the calculated average value not exists in a signal value series, then find the position of signal sample point with most approximate value to an average value and takes the value of that point as interpolation point N_k.

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3. Research method

3.1 Simulation signal

In order to explain the effectiveness of EMD-average method proposed in this paper, we consider a synthetic test signal consisting of three sinusoidal components.

$$f(t) = \frac{1}{3}\left[\cos(\omega_1 t) + \cos(\omega_2 t) + \cos(\omega_3 t)\right] \tag{18}$$

$$\omega_1 = 20\omega_0, \omega_2 = 15\omega_0, \omega_3 = 10\omega_0, \omega_0 = \frac{\pi}{256} \tag{19}$$

In this example, the signal has a sampling number of 4097 with 1 interval.
In order to calculate correct IMFs, the decomposition process is repeated until ε reaches 10^{-16}.
Herein ε is the ratio of the mid value to the selected signal.
The IMFs based on classical EMD method shows in Figure 2.
The frequency spectrums of IMFs based on classical EMD method shows in Figure 3.

Figure2. The IMFs based on Classical EMD

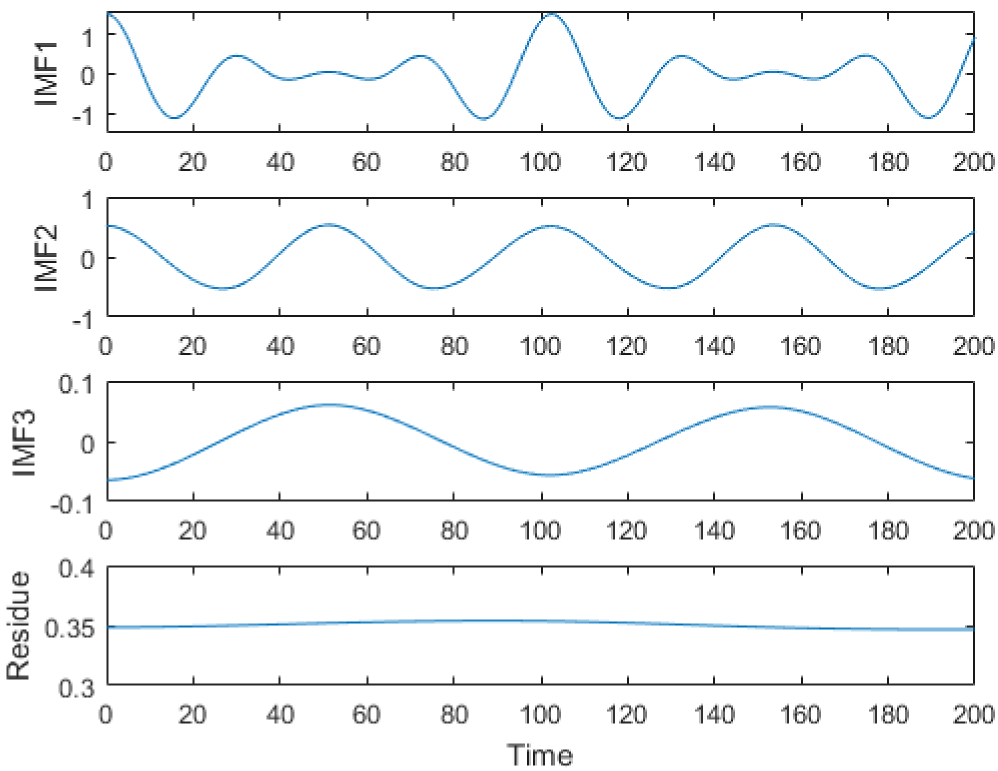
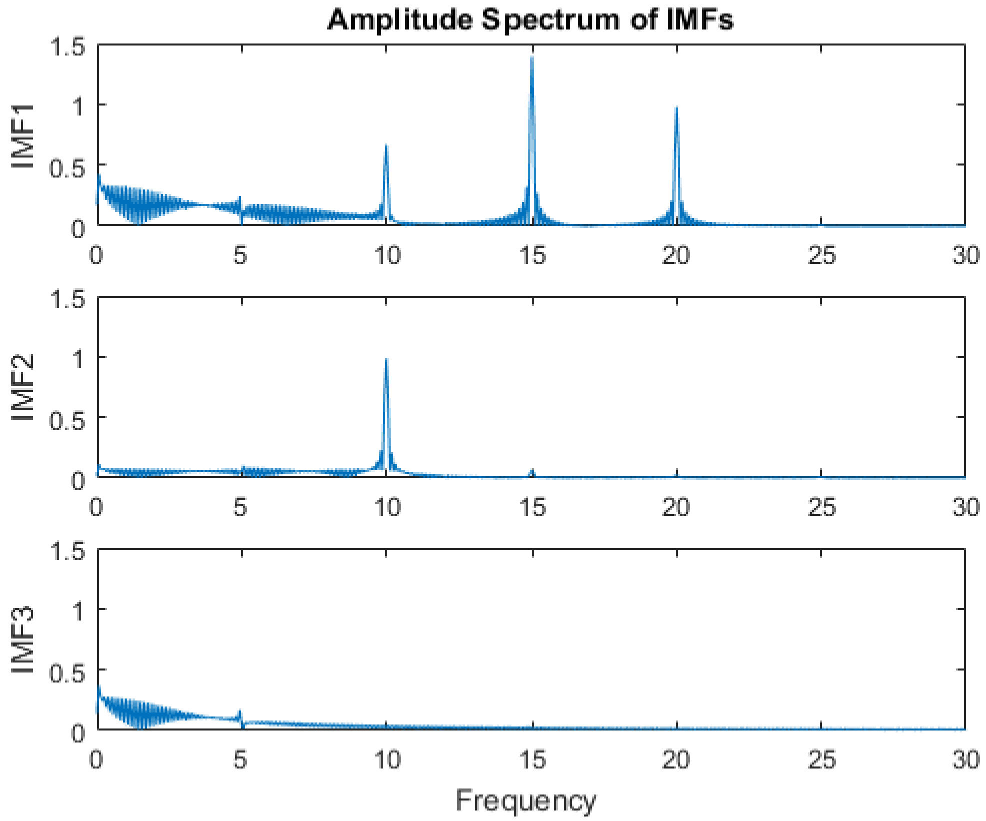


Figure3. Frequency Spectrums of IMFs based on Classical EMD Method



The IMFs based on EMD-midpoint method shows in Figure 4.
The frequency spectrums of IMFs based on EMD-midpoint method shows in Figure 5.
The IMFs based on EMD-average method shows in Figure 6.
The frequency spectrums of IMFs based on EMD-average method shows in Figure7.

Figure4. The IMFs based on EMD-Midpoint Method

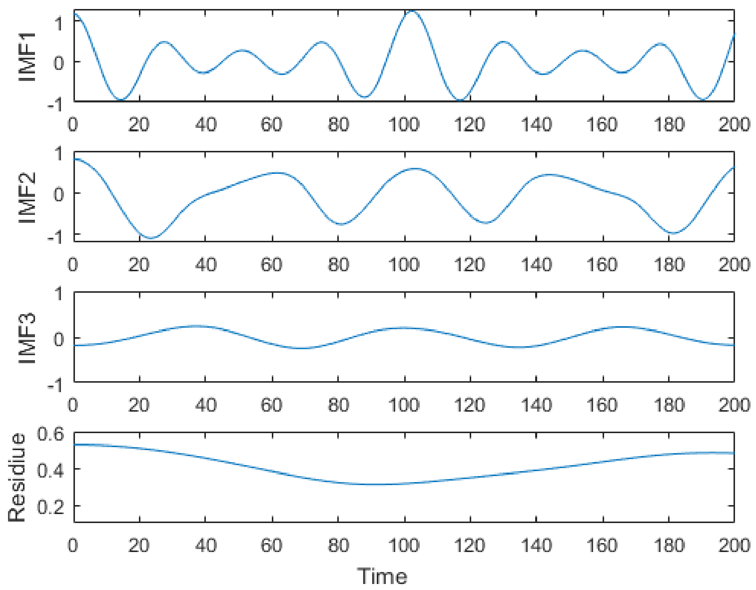


Figure5. Frequency Spectrums of IMFs based on EMD-Midpoint Method

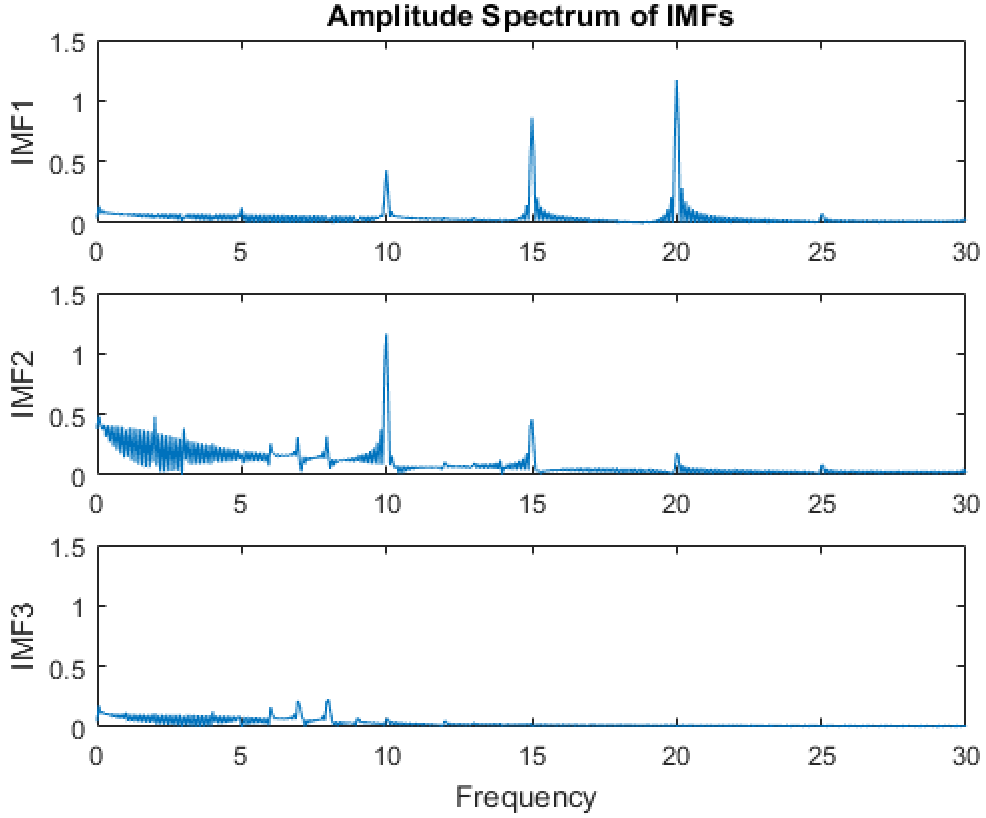


Figure6. The IMFs based on EMD-Average Method

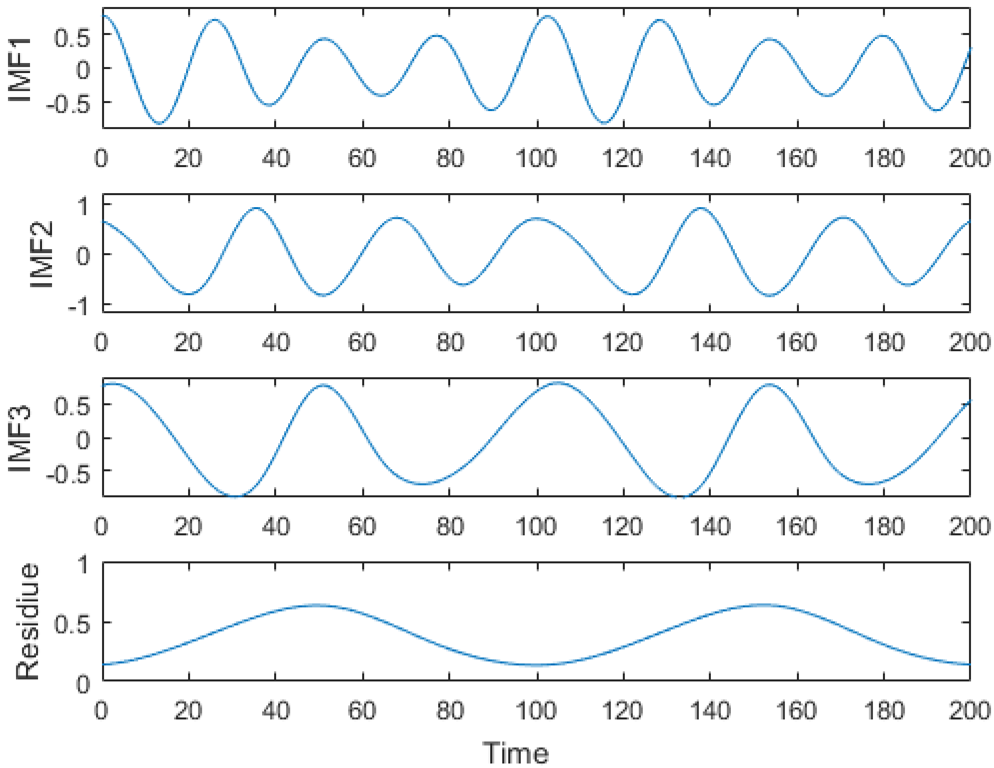
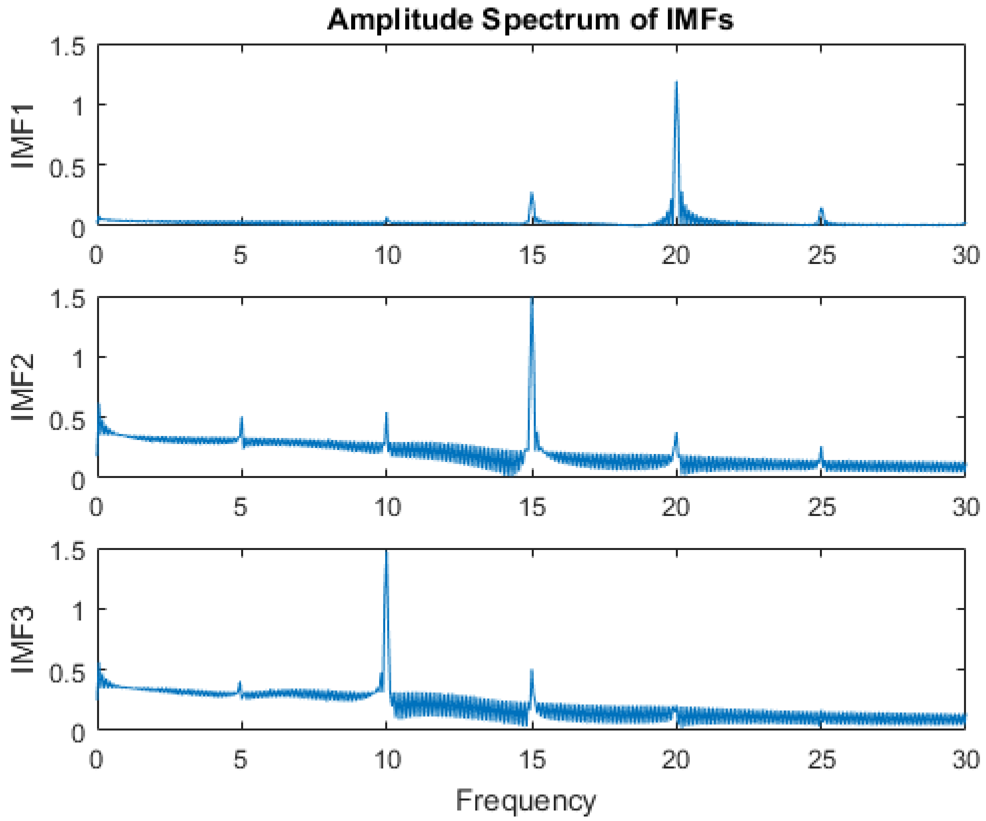


Figure7. Frequency Spectrums of IMFs based on EMD-Average Method



As can see in Figure3 and Figure5, the classical EMD algorithm and EMD-midpoint algorithm are not decomposed the three frequencies components.
However, the EMD-average algorithm decomposed three adjacent frequency components correctly.

3.2 Real vibration signal

MATLAB Simulink block diagram to input the bearing vibration signal into a computer is shown in Figure 8.

Figure8. MATLAB Simulink Block Diagram to Input the Bearing Vibration Signal

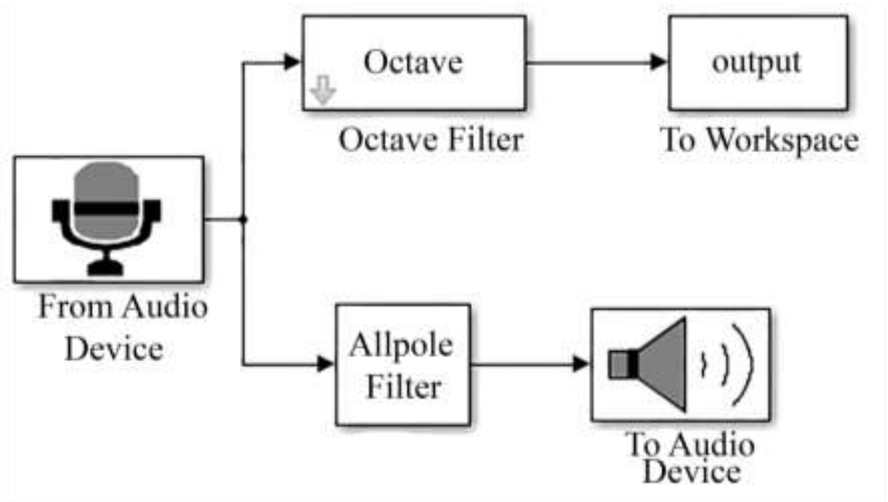
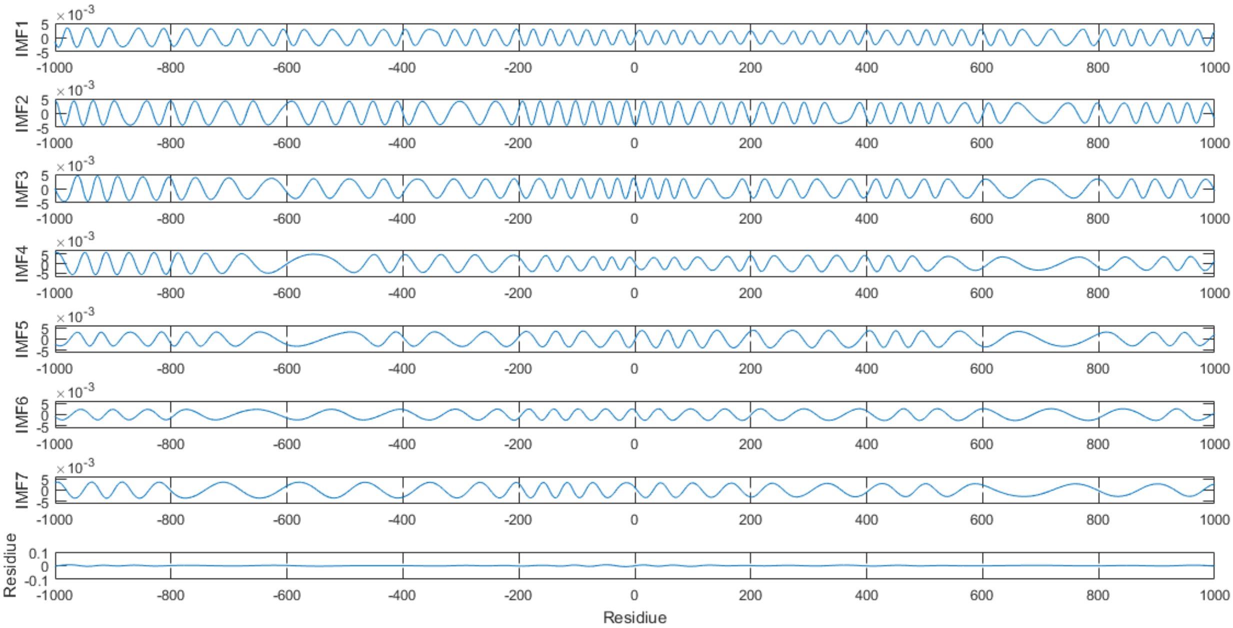


Figure 9. IMFs of Bearing Vibration Signal by Using EMD-Average Method



The bearing vibration signal inputted through the mic port of a computer passes a filter and the digital value data is saved in Workspace. The EMD process is processed on MATLAB using those digital value data. Figure9 shows IMFs of bearing vibration signal by using EMD-average method.

3.3 Discussion

The repetition number of proposed EMD-average algorithm decreased by 1/2 compared to the classical EMD.

The decreases in the repetition number EMD-average algorithm is because, unlike the classical EMD that found the mean values of the lower and upper envelopes at each time, the EMD-average algorithm converges to a monotone function faster by calculating the average values of the maxima and minima.

As the repetition number is few, the time required for calculation is short rather than classical EMD method.

The EMD-average method can't effectively decompose a frequency components of signal strongly corrupted by various noises, but it seems that may overcome the problem by combining filtering technique.

4. Conclusion

In this paper, a methodology for tachometer-free bearing fault diagnosis under time-varying rotating speed condition by using EMD-average method and HT was proposed.

Bearing fault can be effectively detected through the instantaneous frequencies resulting from the HT.

The computational time of the bearing faults will be much reduced when use the EMD-average algorithm, so this technique can be further applied to the vibration signal, speech signal and EEG signal analysis.

Furthermore, the research of fault diagnosis for various types of bearing by using a vibration signal is being investigated.

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